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Exploiting high-resolution data to investigate the characteristics of water consumption at the end-use level: A Dutch case study

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ABSTRACT

In the water industry, an accurate estimation of end-use water consumption is helpful for the implementation of efficient water systems and water-saving technologies. This study aimed to explore the characteristics of water consumption at nine households north of Amsterdam (the Netherlands), subjected to water consumption monitoring at high temporal resolution (i.e. 1 s). Overall, 36,297 water-use events monitored over about 447 days were automatically segmented into 44,115 individual events by means of a new rule-based filtering algorithm, and then labelled by expert analysts. A multi-stage analysis was then conducted in order to evaluate daily per capita end-use water consumption, daily end-use profiles, average end-use parameter average, and their statistical distributions. The results achieved provide insight into the features of end-use consumption, confirming that the largest components are typically related to showers/bathtubs, toilets, and washing machines, whereas different end-use parameter distributions can emerge.

1. .Introduction

Water distribution systems are being ever more stressed due to climate change, population growth, and urbanization, which are increasingly influencing water availability in several regions [1–4]. Periodic water shortage has already affected hundreds of millions of people in areas where there is no longer a balance between water supply and demand [5,6], leading to a progressive depletion of the available water resources. In this context, strategies have to be adopted to cope with water shortages and ensure water availability to future generations [7,8]. These can range from imposing water-use restrictions to controlling leakages, revising water pricing, tailoring water rates, introducing smart water policies, promoting incentives for the installation of efficient appliances or adoption of water-reuse technologies, informing, and educating [9–11]. However, most of the above-mentioned strategies to increase water system efficiency and resiliency cannot generally be implemented if an accurate estimation of water consumption – i.e. an in-depth knowledge of water consumption drivers and variations in space and time – is not available [12–16]. Therefore, in recent years, many studies have been conducted with the aim of exploring the characteristics of water consumption. They have demonstrated that consumption is typically affected by a variety of climatic, geographic, economic, sociodemographic, and behavioural factors [17–19]. By way of example, studies exploring climatic drivers of water consumption reveal that the latter can be significantly affected by rainfall and temperature [20–25], whereas the scarce availability of water resources in some geographical contexts can directly limit the amount of water consumed by users [26–28]. Moreover, the influence of economic or sociodemographic factors such as income, water prices,

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occupation, and level of education has been proved [29–33]. Behavioural factors may have impacts on water consumption as well: in greater detail, it has been widely shown that water demand is generally characterized by a daily or weekly pattern reflecting people's typical habits and lifestyles [31,34–37]. However, the way in which people consume water may be significantly altered by emergency situations, disasters, or exceptional circumstances, as demonstrated, for example, by a number of studies exploring how the restrictive measures recently imposed in many countries to prevent the spread of COVID-19 have impacted on water use [38–41].

In the last two decades, a noteworthy contribution to the investigation of water consumption and its drivers has been given by smart metering. Specifically, smart meters have made water consumption data available at very high spatial and temporal resolutions, i.e. up to the user or end-use (micro-component) level, and from sub-daily up to a few seconds, respectively [42,43]. The availability of data at such a level of spatiotemporal detail allows water utilities to gain a better understanding of when and how water is used [44], detect domestic leakages [45] or other anomalies [46,47], and provide water-use feedback to users, thus inducing them to save water [10,48]. Smart meter data also allow the development of a variety of models and technologies for water reuse and recycling (e.g. Refs. [49–51]), as well as methods for automated water end-use disaggregation and classification (e.g. Refs. [34,52–59]), and urban- (e.g. Refs. [60–63]) or user-level (e.g. Refs. [64–66]) water demand models capable of simulating and forecasting water consumption patterns for different residential and non-residential contexts. The above tools have been proved to significantly support water utilities in making strategic assessments in the field of short- and long-term planning of water supply and distribution systems [67]. However, despite their relevance, it is worth noting that, from an operational standpoint, water reuse and user-level demand models generally have to be calibrated, validated, or parametrized with water consumption data at the end-use level, which may be unavailable to water utilities and researchers. The availability of water consumption data at the level of end use would also allow other applications in the field of water systems management, enabling water utilities to tailor water pricing in order to prevent excessive water use and develop action plans to promote sustainable and aware behaviours towards water consumption [68,69].

The current study aimed to exploit high-resolution data to investigate the characteristics of end-use water consumption at nine households located north of Amsterdam (the Netherlands), in which smart water-use monitoring at 1-s temporal resolution and with 0.1 L/pulse accuracy started in 2019. In greater detail, this study seeks to answer four main research questions: (1) *Which end uses of water most greatly affect overall household consumption?* (2) *How are water end uses distributed throughout the day?* (3) *Which of them are typically characterized by the longest duration, the largest consumption, the greatest flow rate, and the highest daily frequency of use?* (4) *What is the statistical behaviour of the above end-use parameters?*

From an operational standpoint, the aggregate water consumption observed over about 447 days of monitoring was automatically pre-processed by means of a rule-based algorithm for the segmentation of combined water uses, which allowed 44,115 individual end-use events to be identified. These, in turn, were manually labelled by expert analysts. A multi-stage approach was then adopted to answer the above research questions and therefore investigate daily per capita end-use water consumption, daily end-use profiles, average end-use parameter values and their probability distributions. Finally, the results obtained were compared against those of other end-use studies conducted with reference to similar or dissimilar geographical contexts. Indeed, studies investigating the features

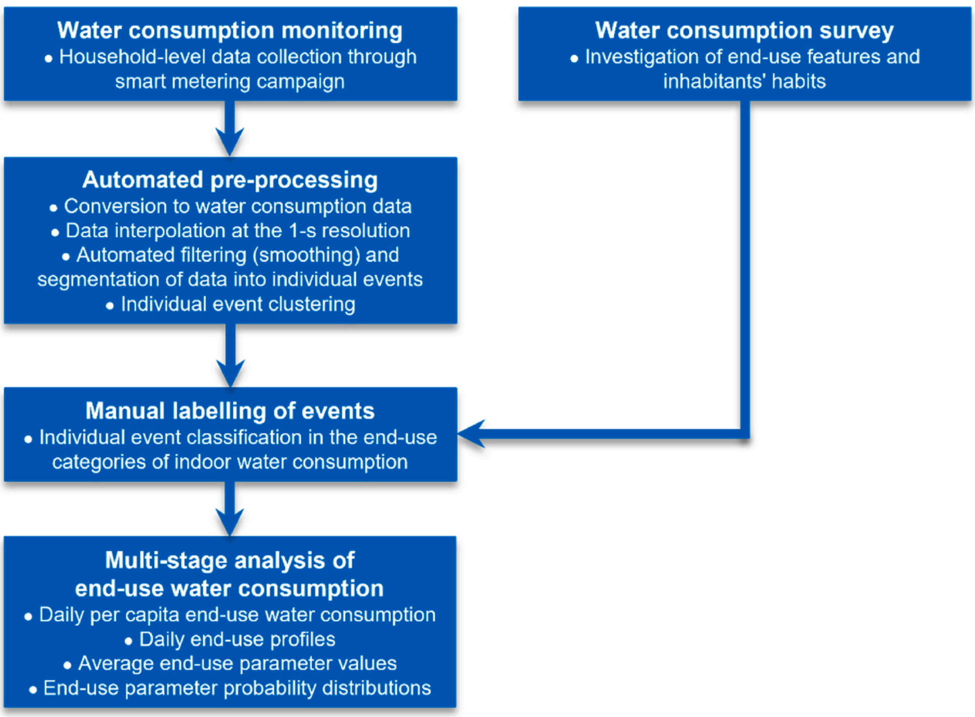

Fig. 1. Methodology structure.

of end-use water consumption in the Netherlands are available in the literature (i.e. [70–74]). However, in all these cases, water consumption characteristics and end-use parameter values were estimated based on coarse-resolution (e.g. monthly) water meter readings and by relying on surveys about water use submitted to a sample population. To the authors' knowledge, this study is the first in which end-use water consumption in the Netherlands was explored by directly exploiting high-resolution data collected in field. Furthermore, the current study investigated aspects – such as the daily profiles of end-use water consumption and the statistical distributions of all end-use parameters – which go beyond the results typically reported in the end-use studies available in the literature (e.g. Refs. [31,34,75–78]). In fact, the outcomes of these studies are typically limited to general considerations on daily average per capita end-use water consumption and the average end-use parameter values, and they seldom include an in-depth statistical analysis of all end-use parameters.

In the following sections, the water consumption monitoring procedure adopted and the multi-stage method followed to achieve the goal of the study are presented (*Materials and methods*). The results obtained with reference to the overall group of households selected are then reported and discussed (*Results and discussion*). Finally, the key findings of the study, along with recommendations for future research, are highlighted (*Conclusions*).

2. Materials and methods

This section includes a description of the measurement campaign conducted to obtain high-resolution water consumption data and the main phases of the methodology (see Fig. 1) applied to answer the study research questions. In greater detail, the high-resolution monitoring of aggregate-level water consumption was first carried out with regard to a group of selected households. Second, the raw data collected were converted and subjected to linear interpolation in order to obtain water consumption time series at the 1-s temporal resolution. Third, each water use detected in the aggregate water consumption time series was segmented into individual events by means of a rule-based, automated filtering algorithm, and then manually labelled by expert analysts based on the consumption features (e.g. duration, volume, time of occurrence, etc.) and relying on the results of water consumption surveys submitted to household inhabitants. Fourth, the obtained end-use water consumption dataset was subjected to a multi-stage analysis aimed at exploring its most relevant characteristics: daily per capita end-use water consumption, daily end-use profiles, average end-use parameter values, and end-use parameter probability distributions.

2.1. Materials

2.1.1. Water consumption monitoring

The high-resolution monitoring of water consumption started in mid-2019 and went on until early 2020, i.e. before the adoption of restrictive measures to limit the spread of the COVID-19. Overall, $N_H = 9$ households located north of Amsterdam (the Netherlands) were selected for monitoring, among those owned by water utility employees who had previously agreed to take part in the research (due to privacy reasons). Specifically, households with different number of inhabitants and family types were considered, in order to explore the characteristics of water consumption with regard to different socio-demographic contexts. The main features of each household subjected to water consumption monitoring are included in Table 1.

Table 1
Characteristics of the monitored households.

Household	Number of inhabitants	Children or teenagers (0-18)	Adults or seniors, part-time Workers (19+)	Adults or seniors, full-time workers (19+)	Adult or seniors, unemployed or retired (19+)	Monitoring start	Monitoring end	Monitoring period (days)
H1	4	1	1	2	0	4 July 2019	4 October 2019	94[a]
H2	4	2	0	2	0	8 November 2019	9 January 2020	63
H3	4	0	2	2	0	8 November 2019	10 January 2020	64
H4	4	2	0	2	0	8 November 2019	10 January 2020	64
H5	4	0	3	1	0	12 November 2019	11 January 2020	62
H6	4	2	0	2	0	10 January 2020	31 January 2020	22
H7	2	0	1	1	0	13 January 2020	25 February 2020	44
H8	4	2	0	2	0	16 January 2020	4 February 2020	20
H9	5	2	0	3	0	17 January 2020	28 January 2020	12

[a] Only 73 days were considered in the current study. Specifically, 21 days with no water consumption due to inhabitants' absence were observed.

Monitoring systems made up of Itron® CENTRON R400 smart water meters with 0.1 L/pulse accuracy and IoTSensReader® devices for remote data collection were installed at each household water inlet point. It is worth noting that the above-mentioned monitoring systems recorded the number of pulses produced over time (and, specifically, over 1- or 2-s time intervals) by each water meter, so a pre-processing of data was initially required to convert this information into water consumption data (L/min).

Overall, raw data were recorded over a total of about 447 days, albeit with different monitoring periods based on the household concerned. Specifically, the number of monitored days ranged from a maximum of 94 days in the case of household H1 to a minimum of 12 days in the case of household H9. Indeed, although the study was initially intended to be conducted by monitoring each household for at least one month, data collection periods were reduced considerably in some cases due to periods of inhabitants' absence (thus showing null consumption) or malfunctioning in the monitoring system (thus including data gaps). However, the duration of all monitoring periods is in line with that reported in many similar studies, i.e. 2–4 weeks [34,75,76,78]. Specifically, this duration has generally been considered as sufficient in order to gain insight into the seasonal water use behaviour of people in individual households.

2.1.2. Water consumption survey

In addition to the smart monitoring of water consumption, surveys about the main features of water end uses and inhabitants' behaviours in terms of water use were submitted to the residents of households H1-H9. Specifically, the survey sent to each household was designed in order to gather information about: (1) family composition, i.e. number of inhabitants, age range, and employment (as shown in Table 1); (2) presence, type, and characteristics of domestic end uses (i.e. dishwasher, washing machine, mixer or knob taps, dual-flush toilet, and bathtub); (3) average frequency of use of the dishwasher, washing machine, and shower/bathtub; and (4) outdoor or other special water uses (e.g. garden taps, active irrigation systems, etc.)

The analysis of the replies sent back by the inhabitants of households H1-H9 revealed that:

1. Households were occupied by 2–5 people in the period concerned, including children, teenagers, and adults or seniors (part- or full-time workers). More in detail, the absence of unemployed or retired residents resulted in a general absence of continuous and distributed water uses throughout the day (except during weekends or holidays), since all the residents typically spent at least a half-day away, at work or school.
2. All the households are equipped with a washing machine and a dishwasher, except household H5 (for which no information about dishwasher presence was given).
3. Only households H1, H3 and H6 are equipped with a bathtub, although only the inhabitants of households H1 and H3 declared that it is used sometimes.
4. Households H1, H3, H6 and H7 are equipped with garden taps, but only the inhabitants of household H6 declared that it was occasionally used during the monitoring period (mainly for washing bicycles and not for irrigating).

2.2. Methods

2.2.1. Automated pre-processing: data conversion and interpolation

The raw data collected in the households considered in the case study (i.e. number of pulses over time) were initially converted to water consumption data according to Equation (1):

$$Q_{i,t} = \frac{a\, n_{i,t}}{d_{i,t}}\, CF \tag{1}$$

where $Q_{i,t}$ (L/min) is the average flow rate observed at the water inlet point of the i-th household ($i = 1, \ldots, 9$) during the t-th time interval of the monitoring period ($t = 1, \ldots, T_i$), a (0.1 L/pulse) is the accuracy of the Itron® CENTRON R400 smart meter used for monitoring, $n_{i,t}$ is the number of pulses counted by the water meter installed at the water inlet point of the i-th household during the t-th time interval, $d_{i,t}$ (s) is the length of the time interval (typically 1–2 s), and $CF = 60$ is a conversion factor allowing flow rate conversion from L/s to L/min. It is worth noting that – most of the domestic water uses being typically characterized by durations of one to a few minutes (as also demonstrated in the following sections) – flow rate values are expressed in L/min to make it easier to figure out which consumed water volumes per use are potentially relatable to different flow rate values.

Specifically, the application of Equation (1) led to high-resolution (i.e. 1 or 2 s) aggregate water consumption time series. These time series were first subjected to linear interpolation to obtain a homogeneous set of water consumption data at the 1-s temporal resolution for all the households. Linear interpolation was automatically carried out by using MATLAB R2019a® programming software.

In addition, all water use events (i.e. time periods characterized by a positive flow rate and isolated from other events by a time interval of at least 1 s with no consumption) of a duration of only 1 s and volume of 0.1 L were removed from the 1-s resolution time series obtained. In fact, these events – characterized by individual water meter pulses and reasonably assumed to be due to pulse conversion or meter inaccuracies – were likely to be unrelated to any actual end-use event. A total of 36,297 water use events of a duration longer than 1 s and volume larger than 0.1 L were observed in the water consumption time series of the N_H–monitored households.

2.2.2. Automated pre-processing: event segmentation and clustering

During the monitoring period, the Itron® smart water meters were installed at the water inlet point of each household selected. As a result, the water consumption time series obtained are representative of the total amount of water entering the households each second, with no information about the number and type of devices producing water inflow. Therefore, both individual and combined

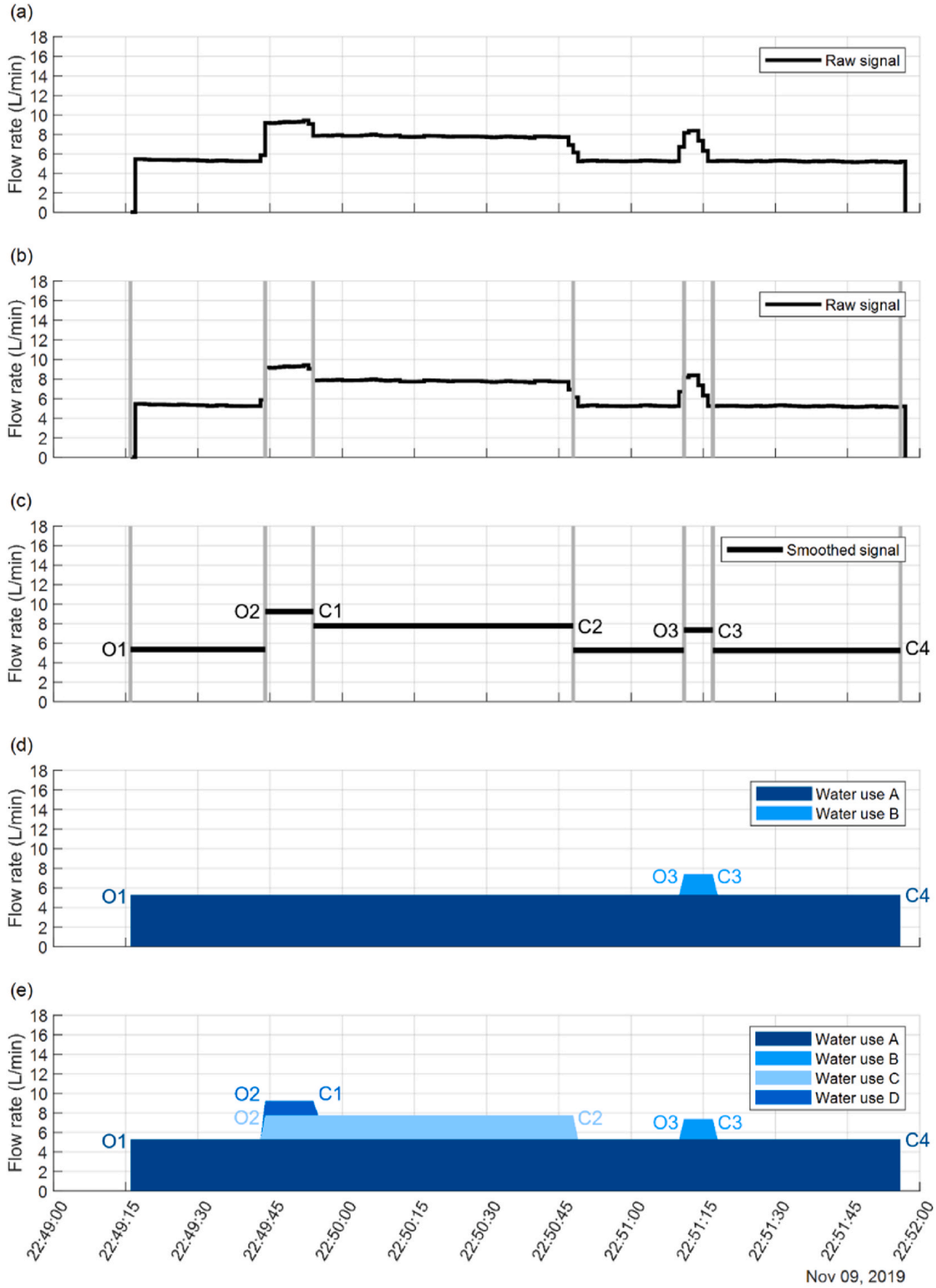

Fig. 2. Automated methodology for water use segmentation into individual events. The combined water use reported by way of example was observed in household H3 and subsequently labelled by the analysts as shower and tap use (water use A and water uses B, C and D, respectively).

water use events were included in the (raw) aggregate water consumption trace of households H1-H9.

In the light of the above, a new, rule-based, automated method for the segmentation of combined water uses into individual uses was developed and applied to each event detected in the aggregate water consumption time series. Automated segmentation was carried out with the aim of providing the analysts a dataset of individual water uses to label without the need to manually segment combined water uses into individual events. In greater detail, the method is based on the following assumptions (similarly adopted by Buchberger et al. [79]): (1) individual water uses are typically characterized by a constant (or nearly constant) flow rate, so they can be described by a rectangular shape in the time-flow plane (whose respective area indicates the volume of water consumed); and (2) combinations of individual uses (i.e. combined events) generally appear as composite rectangular shapes due to partial overlaps of individual uses.

The main structure of the automated method for individual event segmentation is described below and shown in Fig. 2:

- Each water use event (i.e. each portion of the raw aggregate water consumption time series with a positive flow rate) is considered in turn (Fig. 2a). A moving window of limited width (e.g. 3 s) is used to filter the raw time series based on a moving average technique. Specifically, if an abrupt flow rate variation is observed in the raw signal – i.e. if the absolute difference between the average flow rate obtained by means of the moving average techniques at time *t* (s) and that obtained at time *t-1* (s) exceeds a threshold value (e.g. 1 L/min) – this is related to a new opening or closing manoeuvre.
- All the time instants related to the occurrence of opening or closing manoeuvres are considered to split the raw time series into sub-periods with a nearly constant flow rate (Fig. 2b).
- The raw time series is smoothed based on the average value of flow rates observed in each sub-period (Fig. 2c). Moreover, the magnitude (i.e. flow rate variation) of each opening (*O*) and closing (*C*) manoeuvre detected is calculated. It is worth noting that, in the case of non-combined water uses, only two manoeuvres (i.e. an opening and a closing manoeuvre of the same magnitude) are detected by the algorithm, due to the presence of an individual end-use event. In the case of combined water uses, by contrast, more than two manoeuvres (at least three) are detected.
- As far as combined water uses (i.e. water uses composed of more than one individual event) are concerned, a first group of individual events making up the water use considered is identified through the direct matching of opening and closing manoeuvres of similar magnitude (Fig. 2d): in turn, each opening manoeuvre is matched to its most similar closing manoeuvre, i.e. the manoeuvre associated with the most similar flow rate variation. Moreover, the portion of the combined event between the time instants of occurrence of the two matched manoeuvres is considered as an individual water use event (characterized by a flow rate equal to that of the two matched manoeuvres). The detected individual event is then removed from the smoothed time series.
- In the event that not all the manoeuvres are directly relatable (e.g. in the case of manoeuvres of different magnitude, or combined water uses for which a different number of opening and closing manoeuvres are identified), the residual portion of the smoothed time series is segmented through horizontal cuts (Fig. 2e). In this case, two (or more) closing manoeuvres are relatable to a single opening manoeuvre (or vice versa).
- All the (combined and non-combined) events are removed from the raw water consumption time series, and the related set of individual events detected are considered instead.

The effectiveness of the automated method for the segmentation of water consumption data observed in households H1 H9 into individual events was first checked by testing its performance with regard to a series of 50 combined uses – including from one to four

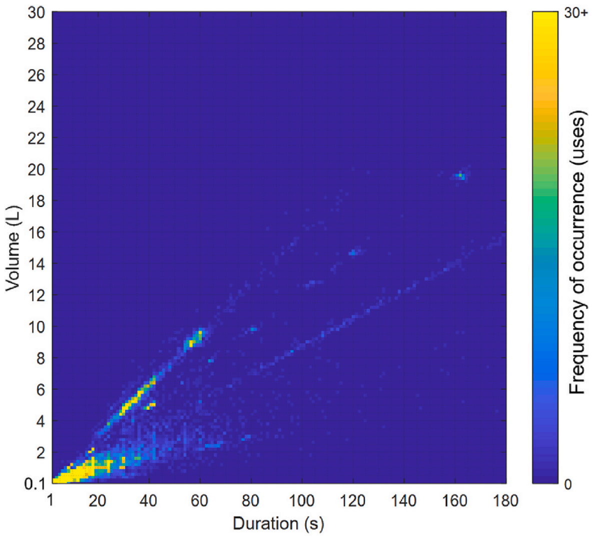

Fig. 3. Household H3 individual water use clustering based on event duration and volume. Individual uses spread over lines are related to human-controlled end uses (e.g. taps, showers), whereas hotspots are related to fixed-volume or automated end uses (e.g. toilet flushing, appliance uses).

individual end-use events – for which segmentation could be reasonably verified by the analysts. However, it is worth specifying that the lack of a dataset of (known) combined water use events to use as a benchmark precluded a full evaluation of the overall performance of the method in successfully segmenting the combined water uses. Also, different results may be obtained where the method is applied with different threshold values (e.g. 5-s wide moving window, or a minimum flow rate variation during opening and closing manoeuvres of 2 L/min).

Overall, the application of the method for the segmentation of the combined water consumption data observed in households H1-H9 in individual events led to an increase in the number of water uses from 36,297 (4,319 of which combined, i.e. 11.9%) to 44,115. More specifically, the 4,319 combined uses detected were automatically segmented into 12,137 individual events, indicating that, on average, each combined water use is composed of 2.81 individual end-use events.

Once the set of 44,115 individual end-use events had been obtained, a clustering analysis was performed in order to provide the analysts with further information for event labelling. In greater detail, for each household, the frequency of occurrence of individual events was explored by locating each event on the duration-volume plane, i.e. by evaluating the number of events falling within each cell of a duration-volume mesh based on event duration and volume of water consumed (as shown in Fig. 3, where the results of household H3 water use segmentation are considered by way of example). The analysis revealed that, in general: (1) water use events were typically below a line whose slope is equal to the maximum flow rate that can be provided by the domestic end uses of the household considered; (2) some events were spread over lines and they were most likely related to human-controlled end uses (due to different durations and the constant flow rate); (3) some other events were lumped into single hotspots and they were most likely related to fixed-volume or automated end-use events (e.g. toilet flushing or appliance uses). Specifically, the above analysis allowed the obtainment of helpful information about the possible end-use category of individual events. This information was considered – along with the information provided by the household inhabitants through surveys – when individual event labelling was conducted (as detailed in the following subsection).

2.2.3. Manual labelling of events

All the individual uses resulting from the automated segmentation of the water consumption trace observed in households H1-H9 were manually labelled, i.e. assigned to specific end-use categories. Event labelling was carried out with the aim of obtaining a water use dataset not only at high temporal level of detail but also at high spatial level of detail (i.e. end-use level).

More in detail, classification was conducted based on engineering judgment and relying both on the information obtained by clustering the events in the duration-volume mesh and that obtained from the replies of water use surveys submitted to the inhabitants. Specifically, events were individually classified based on: (1) physical features of water use (duration, volume, flow rate); (2) time of occurrence; (3) frequency of occurrence of events with similar characteristics; and (4) temporal distance from other events (with similar or dissimilar characteristics). In particular, the following $N_{EU} = 5$ end-use categories were assumed for labelling: *dishwasher*, *taps*, *washing machine*, *shower/bathtub*, and *toilet*. Additionally, all the events whose characteristics did not allow high-confidence classification were labelled as *uncertain* uses. It is worth noting that shower and bathtub uses were considered together in this study due to: (1) the similarity in duration and volume per use between these two categories, making manual discrimination rather difficult in most of the cases; (2) the current tendency of people to mostly use the bathtub for having showers instead of baths, by basically activating the same tap; and (3) the limited use of the bathtub in the households concerned, as reported in the surveys.

From an operational standpoint, classification was carried out by visualizing each event – along with its features – by means of MATLAB® R2019a programming software. Two analysts with prior experience in manually classifying residential water use events (i.e. researchers who had taken part in similar research carried out by Mazzoni et al. [58]) were selected for labelling. In greater detail, labelling was first performed by one of them, considering each individual event in turn (along with its characteristics and position in the aggregate water consumption time series). To avoid bias, the results were then checked and supervised by the other analyst. In the event that the opinion of the latter was not in line with the decision of the former, classification of the water use concerned was jointly discussed and revised accordingly. If, after discussion, an agreement between the two analysts was not reached, the individual end-use event concerned was classified as *uncertain* use. Specifically, a set of rules was applied by the two analysts to perform manual labelling. By way of example, shower/bathtub uses were searched among those infrequent uses – either continuous or composed by many shorter events separated by limited periods of flow interruption – lasting several minutes and characterized by medium (or high) consumption and constant (or nearly constant) flow rate, thus spread over the same line of the duration-volume plane. Similar rules were also adopted to identify tap uses, even though by considering shorter durations, lower volumes, a higher flow-rate variability, and a more frequent daily use. Toilet and appliance uses, by contrast, were searched among the repeated blocks with a constant flow rate and related to lumped durations and volumes, in the light of the fact that they generally appear as hotspots in the duration-volume plane due to the fixed characteristics of flushing systems and appliance water inflows.

Overall, given that (1) the two analysts were capable of labelling a maximum of 2,000 individual events per working day, and (2) an additional time of nearly 2 h per household was required to cluster individual events and process the information available on the water use surveys, it took a total of about 150 h to perform manual labelling of all the 36,297 individual water use events resulting from the automated segmentation phase.

2.2.4. Multi-stage analysis of end-use water consumption

The primary objective of the current study was to explore the characteristics of end-use water consumption in the households considered, highlighting similarities and differences with regard to the end-use data available in the literature for similar geographical contexts. This was achieved through a multi-stage analysis carried out in relation to the overall group of N_H–monitored households in order to compensate for the differences in water consumption behaviours observed in single households.

Specifically, the following four-stage analysis was conducted to address the four main research questions:

1. Evaluation of daily per capita end-use water consumption (L/person/day).
2. Evaluation of normalized (standardized) profiles of daily end-use water consumption. Specifically, daily profiles of water consumption (i.e. a set of 24-hourly water consumption coefficients c_k^t) were calculated for each end use as shown in Equation (2):

$$c_k^t = \frac{\frac{1}{N_H}\sum_{i=1}^{N_H} V_{i,k}^t}{\frac{1}{N_H}\frac{1}{24}\sum_{t=1}^{24}\sum_{i=1}^{N_H} V_{i,k}^t} \tag{2}$$

where $V_{i,k}^t$ is the total hourly water consumption of end use k ($k = 1,\ldots,N_{EU}$) in household i ($i = 1,\ldots,N_H$) over the t-th hour of the day ($t = 1,\ldots,24$). Therefore, the numerator defines the average volume of water consumed by end use k in all the N_H-households at hour t of the day, whereas the denominator represents the daily average water consumption of end use k, calculated considering all the N_H-households. By way of example, a c_k^t–value equal to 2 suggests that – at hour t and with regard to the overall household sample – the water consumption of end use k is twice its daily average.
3. Evaluation of end-use parameter values (i.e. volume per use, duration per use, flow rate per use, and daily frequency of use) and comparison against the values available in the literature. More precisely, the following units of measurements were adopted: *L/use* in the case of volume per use, *min/use* in the case of duration per use, *L/*min in the case of flow rate per use, and *uses/person/day* in the case of frequency of use. It is worth noting that, in this analysis, a minimum temporal distance between two subsequent events of the same category was assumed for each end-use class, above which they were considered as separated water uses. Specifically, a minimum temporal distance of 5 s was considered in the case of taps and toilets, whereas a threshold of 2 min was assumed in the case of showers (given that people may be used to turning off the water several times – and also for some minutes – during a shower). In addition, as far as electric appliances are concerned, dishwasher and washing machine events occurring more than 90 min after the previous ones were considered to be related to different operating cycles (hereinafter denoted as *loads*).
4. Evaluation of end-use parameter empirical distributions and identification of the type (and the parameters) of the best-fitting statistical distribution. In greater detail, the empirical probability density functions (PDFs) of individual households were first obtained through the kernel density estimation for each end-use and parameter distribution. Individual PDF curves were then averaged over all N_H–households to obtain an overall set of empirical PDFs. The average empirical PDFs were then subjected to automated curve fitting by means of MATLAB R2019a® software. Specifically, in accordance with the results reported in similar studies available in the literature – e.g. Blokker et al. [64] and the cited references – five statistical PDFs were considered for fitting: (1) normal; (2) lognormal; (3) exponential; (4) Gamma; and (5) Weibull. The above-mentioned set of continuous PDFs was selected due to the non-discrete nature of the four end-use parameters investigated in this study. The Akaike Information Criterion (AIC) [80] was used to evaluate the goodness-of-fit of each statistical PDF type. The best-fitting PDF was finally selected based on the distribution type characterized by the minimum AIC parameter value.

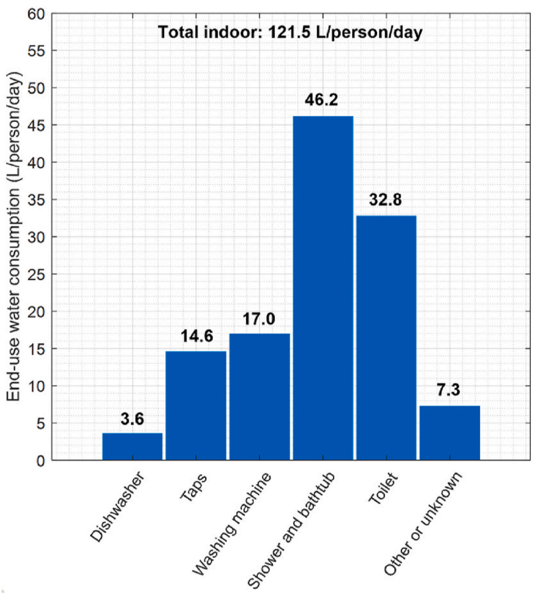

Fig. 4. Daily per capita end-use water consumption in the monitored households.

Table 2
Average end-use parameter values and comparison against the values reported in other Dutch studies.

Study	Water consumption[a] (L/person/day)							Frequency of use[a] (uses/person/day)						Duration per use[a] (min/use)						Volume per use[a] (L/use)						Flow rate per use[a] (L/min)					
	Indoor	D	T	WM	S	B	F	D	T	WM	S	B	F	D	T	W	S	B	F	D	T	WM	S	B	F	D	T	WM	S	B	F
Kanne 2005 [70]	123.6	3.0	20.3	18.0	43.7	2.8	35.8	0.25	–	0.28	0.73	0.05	5.96	–	–	–	7.7	–	–	18.0	–	63.9	–	113.5	8.0	–	–	–	7.8	–	–
Foekema et al., 2008 [71]	127.5	3.0	19.6	15.5	49.8	2.5	37.1	0.25	–	0.28	0.80	0.05	6.27	–	–	–	7.9	–	–	16.5	–	56.9	–	114.2	7.9	–	–	–	7.7	–	–
Foekema and van Thiel 2011 [72]	120.1	3.0	17.7	14.3	48.6	2.8	33.7	0.23	19.59	0.26	0.75	0.05	5.86	–	–	–	8.1	–	–	15.8	–	55.6	–	114.3	7.9	–	–	–	7.7	–	–
van Thiel 2014 [73]	118.9	2.0	15.6	14.3	51.4	1.8	33.8	0.17	20.01	0.28	0.72	0.04	5.90	–	–	–	8.9	–	–	14.3	–	52.9	–	114.5	7.7	–	–	–	7.7	–	–
van Thiel 2017 [74]	107.0	2.5	10.0	14.1	44.2	1.6	34.6	0.17	19.21	0.24	0.69	0.03	5.87	–	–	–	7.6	–	–	13.1	–	53.9	–	112.5	7.7	–	–	–	8.2	–	–
Current Study	**121.6**[b]	**3.6**	**14.6**	**17.0**	**46.2**[c]	-	**32.8**	**0.27**	**13.83**	**0.27**	**0.76**[c]	-	**4.22**	**4.3**[d]	**0.2**	**8.2**[d]	**8.0**[c]	-	**0.8**	**11.4**	**1.2**	**62.9**	**63.6**[c]	-	**6.8**	**2.8**	**4.8**	**7.0**	**7.9**[c]	-	**8.3**

[a] D = Dishwasher T = Taps, WM = Washing Machine, S = Shower, B = Bathtub, F = Toilet.
[b] 7.3 L/person/day are related to *other* or *unknown* indoor uses.
[c] Value referring to shower and bathtub use.
[d] Total duration of water inflow per appliance load.

3. Results and discussion

This section includes a discussion of the results obtained by applying the four-stage analysis (described in the *Materials and methods* section) to investigate the characteristics of the end-use water consumption in the households monitored. All the numerical results presented hereinafter will be expressed with decimal precision, except those related to the daily per capita frequency of use. In this case, centesimal precision will be considered instead, to properly account for end uses which occur with very low daily frequency.

3.1. Evaluation of daily per capita end-use water consumption

As far as the daily per capita water consumption is concerned, an (aggregate) average value of 121.5 L/person/day was observed in the monitored households, the largest part of which tied to the use of showers/bathtubs (46.2 L/person/day, i.e. 38.0%) and toilets (32.8 L/person/day, i.e. 27.0%), as indicated in Fig. 4. Conversely, lower volumes were related to the use of washing machines (17.0 L/person/day, i.e. 14.0%), taps (14.6 L/person/day, i.e. 12.0%), and dishwashers (3.6 L/person/day, i.e. 3.0%), with a residual amount of about 7.3 L/person/day (i.e. 6.0%) classified as *uncertain* use of water.

Overall, the results obtained indicate that, on average, the largest components of daily residential water consumption are related to the use of showers/bathtubs and toilets, followed by washing machines and taps (whose daily per capita water consumption values are generally rather close). This finding is coherent with the results of other end-use studies conducted in similar or different geographical contexts (e.g. Refs. [31,34,70–78]).

As far as individual end uses of water are concerned, it is first worth noting that the results obtained are in line with those reported by the other end-use studies conducted in the Netherlands – i.e. [70–74], the results of which are shown in Table 2 – except as regards the daily per capita water consumption of dishwashers and toilets, which is slightly outside the ranges reported in the other Dutch studies cited (i.e. 2.0–3.0 and 33.7–37.1 L/person/day, respectively). As demonstrated in the following subsection and shown in Table 2, this is mainly due to variations in the daily frequency of dishwasher and toilet use, along with lower average volumes per toilet flush. In addition, larger differences among end uses emerge when the results of the current study are compared against those reported for different countries, such as the United States (i.e. [31,75]) or Australia (i.e. [31,76–78]). For example, the toilet water consumption reported in this study is considerably lower than the values shown in the American studies (49.7–70.0 L/person/day) and higher than the values indicated in the Australian ones (14.3–31.0 L/person/day), whereas higher water consumption values for washing machines and taps were observed in all the aforementioned American and Australian studies (20.7–56.9 and 17.4–41.2 L/person/day, respectively). It is believed that the reported differences are partially due to different levels of technological development reflected in the studies concerned – explaining why, for example, the largest consumption associated with toilet use was observed in the most outdated study (i.e. [34]) – and partially to behavioural factors related to water availability and drought risk. The latter aspect could explain, for example, why the lowest toilet water consumption values were observed in the Australian studies. Lastly, no significant

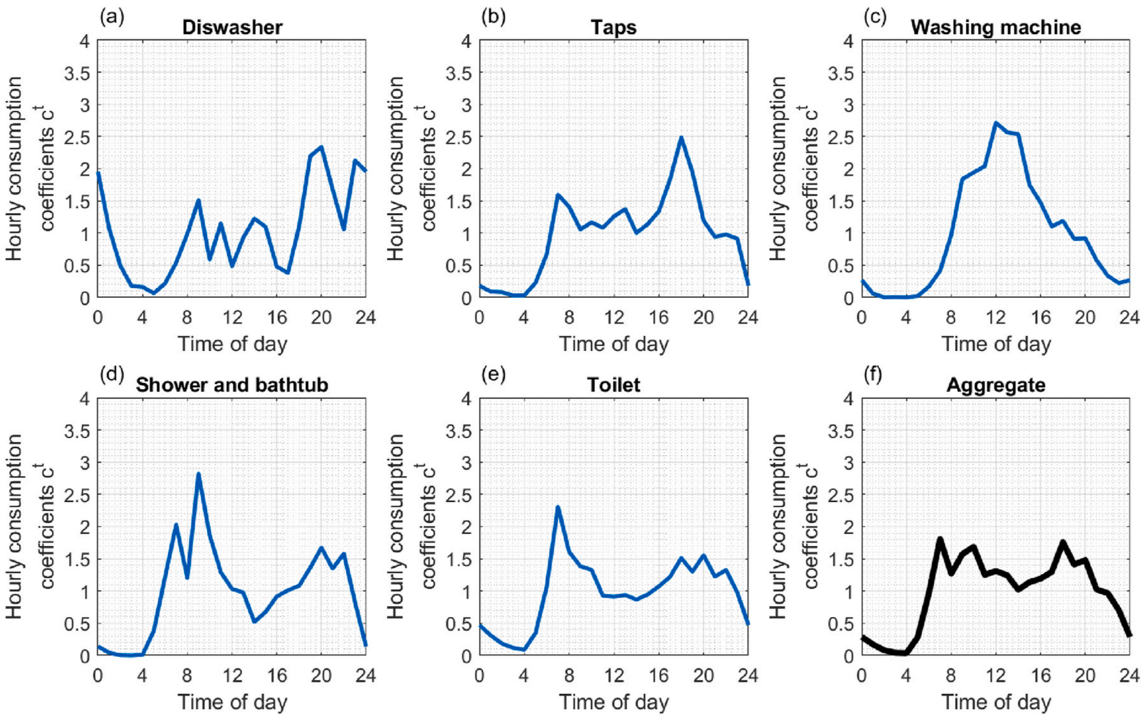

Fig. 5. Daily end-use and aggregate profiles of water consumption.

differences among studies were observed in the case of dishwasher and shower/bathtub uses.

3.2. Evaluation of normalized profiles of daily end-use water consumption

The evaluation of the normalized (i.e. standardized) end-use water consumption profiles revealed, on a daily basis, different hourly distributions of water consumption based on the end-use category considered, as shown in Fig. 5.

On the one hand, it emerged that, as expected, the water consumption of toilets (Fig. 5f) and taps (Fig. 5b) is minimum at night and pretty constant in diurnal hours, confirming that the above end uses generally occur in a constant manner throughout the day (although peaks in water consumption emerge in the morning and at dinner time, respectively, when people are most likely to be at home). On the other hand, in the case of showers/bathtubs (Fig. 5d), water consumption is more concentrated at specific times of the day, these end-uses being characterized by a higher peak in the morning (when people get up) along with a lower peak in the evening (when people come back home). Breaking down water consumption further, two peaks occur in the morning, the first of which at around 7:00 and the second of which at around 9:00. These different behaviours in terms of water use are most likely due to the different profiles of the inhabitants (who include children, students, and part- or full-time workers) and also different habits, such as having showers before or after breakfast time. Furthermore, as far as appliance profiles are concerned, a single peak of water consumption was observed around midday in the case of washing machines (Fig. 5c), whereas a rather heterogeneous profile emerged in the case of dishwasher use (Fig. 5a), although it may be observed that this appliance is typically used around breakfast/mealtime or during the night. Overall, the daily end-use profiles obtained are in line with those shown in the rather limited number of end-use studies including this kind of information (see, for example [31,34,76–78]).

3.3. Evaluation of average end-use parameter values

The availability of high-resolution information about end-use water consumption also allowed an investigation of end-use parameters such as daily frequency of use, volume per use, duration per use, and flow rate per use. End-use parameters were obtained by statistically analysing, in turn, the characteristics of all the events included in each end-use category. Moreover, the results of the analysis were compared against those reported in studies previously conducted in the same geographical area, as shown in Table 2. In this regard, the studies conducted on a three-yearly basis in the Netherlands for the period between 2004 and 2016 [70–74] were considered as a benchmark.

When the frequency of use is considered, it emerged that, on average, taps are activated most frequently (13.83 times/person/day), followed by toilets (4.22 flushes/person/day). Moreover, inhabitants are used to having a shower (or a bath) about three times every four days (0.76 uses/person/day), whereas dishwashers and washing machines are typically loaded with daily (or higher) frequency only in households with at least 3–4 inhabitants (0.27 loads/person/day). As far as the duration per use is concerned, the results show that only shower uses last several minutes (8.0 min/use), whereas the duration of toilet and tap use is only of a few seconds (0.8 min/use – i.e. about 48 s/use – in the former case, and 0.2 min/use – i.e. about 12 s/use – in the latter). It was also observed that, despite the considerably long duration per appliance load (which may last up to 3 h), the total duration of washing machine and dishwasher inflow is only about 8.2 and 4.3 min/load, respectively, revealing that appliances typically work without drawing water in for most of the duration of the load. In addition, considering volume per use, the statistical analysis showed that showers/bathtubs and washing machines are the most consuming end uses, with about 63.6 L/use and 62.9 L/load respectively. They are followed by dishwashers (11.4 L/load), toilets (6.8 L/flush), and taps (1.2 L/use). In greater detail, it is worth noting that, although toilet and tap volumes per use are the smallest, the contribution of these end uses to the total indoor water consumption is significant because of their considerably high daily frequency. Finally, considering flow rate per use, the highest average values were observed in the case of toilets (8.3 L/min), showers/bathtubs (7.9 L/min), and washing machines (7.0 L/min), whereas lower values emerged in the case of taps (4.8 L/min) and dishwashers (2.8 L/min).

In general, the average end-use parameter values are in line with those of previous Dutch studies, albeit with some exceptions. By way of example, the daily frequency of tap and toilet use is slightly lower than the corresponding values reported in other studies [70–74], i.e. 19.21–20.01 uses/person/day and 5.86–6.27 flushes/person/day, respectively. This is most likely due to the fact that all the residents of the N_H-monitored households are students or workers, so they generally spend at least a half-day away, with consequent reduced toilet or tap use at home. In addition, an increase in the frequency of dishwasher use emerged in the current study – resulting overall in an increase in daily per capita water consumption associated with dishwashers – whereas no relevant changes in frequency were observed in the case of washing machines and showers/bathtubs. As far as volumes per use are considered, the value obtained in the current study with regard to dishwasher use confirms the decreasing trend highlighted in the other studies [70–74], whereas an inverse behaviour emerged in the case of washing machine use (despite the similar decreasing trend reported in the above-mentioned studies) where average consumption was nearly 10 L higher than the consumption observed in the last decade (see, e.g. Refs. [72–74]). With regard to toilets, a considerably lower volume per flush was observed in the current study compared to the other values reported [70–74], which may reasonably be attributed to technological advancements. More specifically, 7 of the $N_H = 9$ monitored households have toilets with dual-flush systems, leading to non-negligible water savings per individual flush. Lastly, no relevant differences emerged in the case of shower duration and flow rate per use (i.e. the only end use for which duration and flow rate were investigated in previous studies).

3.4. Evaluation of end-use parameter probability distributions

The findings with regard to the average end-use parameter values were confirmed by the outcomes of the analysis of their empirical and statistical distributions (PDFs). From an operational standpoint, as far as duration per use is concerned, the analysis was carried out by expressing all durations in seconds (s/use, s/load, or s/flush based on the end use considered) and all volumes in litres (L/use, L/load, or L/flush, respectively), whereas the flow rate was expressed in litres per minute (L/min). Moreover, considering the distribution of appliance use duration, it is worth noting that the total length of the periods during which the appliance drew in water was considered, rather than the duration of the overall load. In fact, appliance uses typically involve a number of inflow events lasting a few minutes and taking place between longer periods of time during which the machine does not draw in water. Finally, as regards the daily frequency of use, statistical distributions are expressed in uses/person/day (taps, showers/bathtubs), flushes/person/day (toilets), or loads/person/day (electric appliances), so as to be comparable with the results available in the literature.

The best-fitting statistical PDFs of the overall end-use dataset are shown in Fig. 6 (blue lines) along with details about distribution type and parameters. As expected, the mean of these distributions is in line with the average parameter values shown in Table 2. Statistical PDFs were also compared against their respective empirical PDFs (thick grey lines) obtained with respect to the overall H1-H9 dataset.

Overall, different parameter distributions were estimated, depending on the end use and the parameter considered. More specifically, right-skewed statistical PDFs emerged in most of the cases, fitted by lognormal, Weibull, or Gamma distributions. However, some parameter distributions were fitted by normal or nearly normal curves (e.g. toilet flush duration, shower flow rate, and toilet flush flow rate), indicating that, in these cases, the end-use parameter values were distributed almost symmetrically around the average. An exception is represented by washing machine flow rate values, which were fitted by a slightly left-skewed Weibull PDF.

Moreover, as far as duration and volume distributions are concerned, empirical and statistical PDFs substantially correspond in the case of some end uses (taps, washing machine, shower/bathtub), whereas larger differences emerged for the others (dishwasher, toilet). This deviation between empirical and statistical PDFs of dishwasher and toilet uses is partially due to the limited number of monitored users – making the empirical distribution of parameter values nearly multimodal – and partially due to the limited variability of appliance and toilet parameters in the same household, given that their volume and duration were generally constant. In fact, the parameter empirical PDFs of individual households were considerably narrower than the corresponding best-fitting statistical PDFs

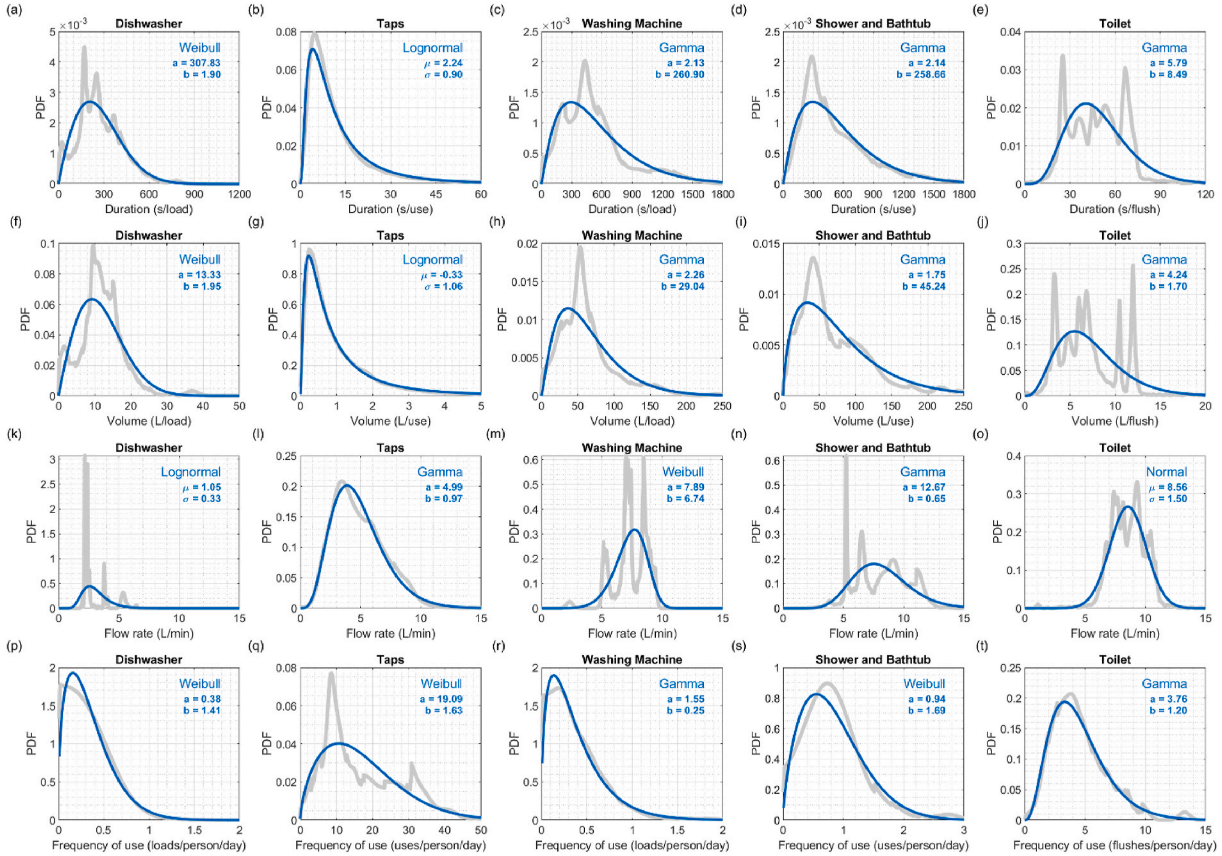

Fig. 6. Empirical (grey) and statistical (blue) PDFs of different end uses and parameters. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

of the overall set of N_H–households.

Differences between empirical and statistical PDFs were also observed in the case of flow-rate distributions, which differed from household to household. These differences emerged for all end-use flow rates and are most likely due to: (1) household location (i.e. pressure head available at the household inlet point); (2) plumbing system layout and age (i.e. pressure head available at the end use); and (3) end-use type (i.e. device make and model). The only exception is represented by the tap flow rate, which was characterized by a smoothed empirical PDF with the absence of multiple peaks. This is most likely due to the fact that taps are typically used in a variety of ways even within the same household (i.e. not only for different durations, but also with manual adjustments in the flow rate).

Lastly, with regard to the daily frequency of use, most of the best-fitting statistical PDFs obtained (nearly symmetrical or right-skewed Weibull or Gamma distributions) closely approximated their respective empirical PDFs. The largest differences were observed in the case of taps, in relation to which a multi-peak empirical PDF – fitted by a slightly right-skewed Weibull curve – was found; this distribution reflects the different behaviours in terms of tap use within households not only as regards timing of use and modulation (see, by way of example, the best-fitting statistical distribution of tap duration per use and flow rate), but also as regards frequency of use.

5. Conclusions

The current study was conducted with the aim of investigating the characteristics of water consumption at the end-use level by exploiting high-resolution data collected at nine households in the Netherlands, differing in terms of occupancy rates, inhabitants' profiles, and available end uses. The study entailed: (1) developing and applying a method for automated data pre-processing (i.e. segmentation of water uses into individual events) and (2) manually labelling the individual events obtained based on engineering judgment and the information available from water consumption surveys submitted to household inhabitants. A multi-stage analysis was then conducted in order to explore the main features of end-use water consumption in the selected households.

Specifically, the following findings emerged:

- The average daily per capita water consumption was of 121.5 L/person/day, with the use of showers/bathtubs and toilets accounting for the largest part of consumption (46.2 and 32.8 L/person/day, respectively), whereas lower consumption was associated with washing machines, taps, and dishwashers (17.0, 14.6, and 3.6 L/person/day, respectively).
- The use of toilets and taps was rather constant during the day, whereas a more concentrated use of showers/bathtubs and washing machines could be observed at specific times of the day. In addition, a heterogeneous daily profile emerged in the case of dishwasher use.
- Taps were activated the most during the day (13.83 times/person/day), followed by toilets (4.22 flushes/person/day), whereas showers/bathtubs and appliances were typically used once or less than once per person per day.
- Only shower/bathtub uses generally lasted several minutes (on average 8.2 min/use), whereas the average duration of toilet and tap uses was shorter than 1 min (0.8 and 0.2 min/use, respectively). In addition, despite the long duration of appliance operating cycles (*loads*), the total duration of inflow is only of a few minutes per load.
- The largest average volumes per use were tied to showers/bathtubs and washing machines (63.6 and 62.9 L/use, respectively), followed by dishwashers, toilet, and taps (11.4, 6.8, and 1.2 L/use, respectively).
- The highest flow rates per use were observed in the case of toilets, showers/bathtubs, and washing machines (8.3, 7.9, and 7.0 L/min, respectively), whereas lower values emerged in the case of taps and dishwashers (4.8 and 2.8 L/min, respectively).
- Different parameter distributions were estimated, depending on end use and the parameter considered. Right-skewed empirical distributions (PDFs) were observed in most of the cases, generally fitted by Lognormal, Weibull, or Gamma statistical PDFs. As expected, the empirical PDFs of manually regulated end uses (e.g. showers/bathtubs and taps) were generally well fitted by the above statistical PDF types, in the light of the fact that the parameters involved basically depend on human habits and their values may cover a rather wide range even within the same household. Conversely, the empirical PDFs of automated or fixed-volume end uses (i.e. electric appliances and toilets) were quite narrow in the case of individual households and nearly multimodal (thus poorly fitted by the above statistical PDF types) with regard to the overall household dataset. This is a consequence of the fact that toilet and appliance parameters are typically not variable within the same household, whereas considerable differences may be observed from household to household.

It is worth noting that the end-use data obtained refer to a limited set of households. In addition, nearly all data were acquired during the in-between or cold seasons, i.e. when outdoor water consumption is typically minimum or null, and some indoor end uses (e.g. taps or showers) may be affected by reductions in the frequency of use. Therefore – and similarly to Refs. [70–74] – the seasonal variability of end-use water consumption was not investigated in the current study due to the lack of extensive data collected during warmer periods. Despite the above, the results obtained may represent a first, helpful benchmark against which to compare the results of future end-use studies including the monitoring of residential water consumption. In fact, unlike other studies conducted on water consumption in the Netherlands (e.g. Refs. [70–74]), which made use of surveys and questionnaires to gather information about water end uses, this study relied on actual water consumption time series collected at high temporal resolution, whilst the information obtained through surveys (which may be unreliable and subjective) was used only to support the analysts during the classification phase. In addition, the current study investigated some end-use water consumption features – such as the statistical distribution of end-use parameter values – which had been previously explored only to a limited degree and which can support the calibration of water demand models available in the literature (e.g. Ref. [53]).

In conclusion, it is believed that the end-use dataset obtained could be used to provide feedback to household inhabitants, thereby increasing their awareness and encouraging a more conscious water use behaviour. By way of example, as far as the households considered in this study are concerned, if inhabitants are aware that much of their domestic consumption is tied to specific aspects, such as the presence of excessively large toilet tanks (e.g. household H2, including a toilet with a capacity of about 12 L), or excessively long showers (e.g. household H4 showers, lasting on average about13.3 min), they might be encouraged to install more efficient or water-saving devices (e.g. dual-flush systems) or change their consumption behaviour (e.g. by adjusting flow or closing taps). The results obtained could also be of interest to water utilities operating in the above geographical context – but not only – since they provide insight into when and where water is typically consumed in the residential sector. This could support intervention plans and strategies not only to optimize water distribution, but also to promote a reduction in water consumption through specific information campaigns or incentives for the installation of more efficient devices. Lastly, the results of the study confirm that a detailed characterization of domestic end-use water consumption and parameters is feasible even in the case of rather limited monitoring periods of ordinary home activity (e.g. two weeks) and that the proposed methodology may be a valid alternative to survey-based analyses of water consumption at the end-use level.

Future studies will focus on enlarging the water consumption dataset in order to explore the characteristics of residential end uses of water over different periods and evaluate the seasonal variability of end-use water consumption. In addition, analyses will seek to investigate the minimum household sample size required to obtain a representative and statistically significant dataset per family cluster. This will allow the end-use results obtained to be scaled up to broader contexts in the field of residential – and, subsequently, non-residential – water consumption. Further developments will also include the definition of guidelines supporting the automated labelling of individual end-use events, with considerable time and human resource savings.

Data statement

The data presented in this study (i.e. high-resolution aggregate water consumption data of the households included in the case study) can be made available on request – and in an anonymized version – from the corresponding author.

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Authors' contributions

Filippo Mazzoni: Methodology, Software, Formal analysis, Writing – Original Draft, Writing – Review & Editing. Stefano Alvisi: Conceptualization, Methodology, Validation, Writing – Review & Editing. Marco Franchini: Conceptualization, Methodology, Writing – Review & Editing, Supervision. Mirjam Blokker: Conceptualization, Methodology, Investigation, Resources, Data Curation, Writing – Review & Editing, Supervision.

All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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